Draft

The Veil of Ignorance Process Tracing (VoiPT) methodology

Version 8

James Copestake
and
Gary Goertz
and
Stephan Haggard

Note: Prepared for a symposium in *Qualitative & Multi-Method Research*. The order of the authors is alphabetical. Thanks to the QuIP team – Fiona Remnant, Rebekah Avard, Marlies Morsink, and Steve Powell – for many discussions.

Introduction

A central problem in all quantitative and qualitative research is the risk of omitted variable bias and cherry picking. What confidence do we have that the researcher is not producing just-so stories: accounts that are biased in favor of the author's causal story over valid theoretical competitors? Analysis of observational data deals with this problem through the inclusion of controls. Experiments deal with selection bias via randomization. Qualitative research lacks similar mechanisms for guarding against biased selection of data.

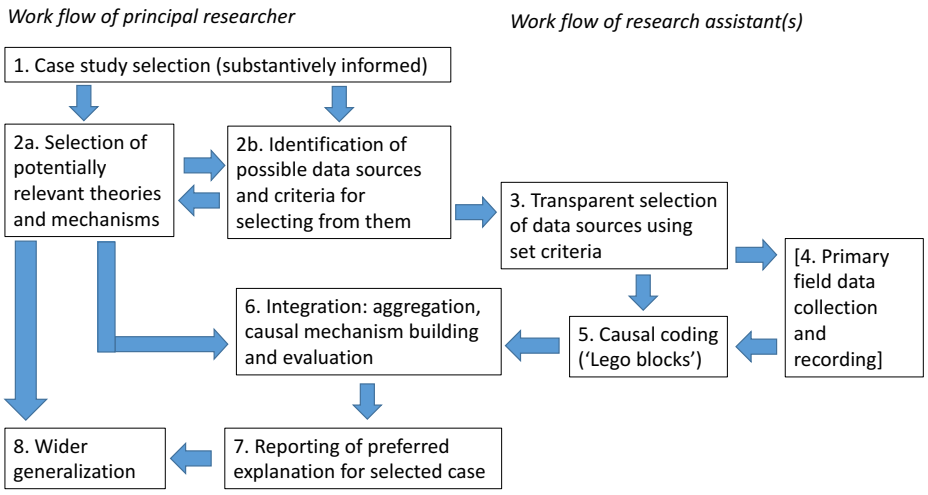
In this paper we introduce an approach to causal mechanism observation and process tracing methodology that addresses these issues. What we call a "veil of ignorance" approach can be used to guide the collection and initial analysis of primary qualitative data for the purpose of process tracing. The approach builds on a causal attribution methodology, known as the Qualitative Impact Protocol or QuIP, developed by James Copestake and his colleagues for use in evaluating development projects (2019).

Our approach starts with the proposition that diverse forms of qualitative evidence – open-ended interviews, primary sources such as archival material, as well as secondary sources – all contain a variety of causal claims. The method seeks to tap these claims for the purpose of causal inference in a systematic and transparent way, reducing possible sources of bias both in identifying sources and extracting information from them.

Core to the veil of ignorance methodology is the separation of the interpretive role of the principal researcher(s) from the task of extracting what might be called "causal claim Lego blocks." This is a radical departure from current practice in process tracing where the two are completely fused: the same researcher determines the sources, looks for causal information in them, and then integrates the findings for the purpose of causal inference. The reference to veils of ignorance arises from a division of labour that allows a research assistant to carry out key data selection and coding tasks without knowledge of the theories, hypotheses and mechanisms being tested. The result is less risk bias arising from priors; as will be seen, this disciplining function is similar in some respects to procedures advanced by Bayesian approaches to qualitative analysis (Fairfield and Charman 2019).

This division of labour is encapsulated in figure 1, which sets out the proposed workflow sequence. As can be seen, it distinguishes clearly between research roles. The role of the principal researcher(s), on the left of the diagram (Boxes 1,2a,2b,6 7,9) are to choose and theoretically frame the case study, provide criteria for credible evidence about the case, and use findings to build understanding of the causal processes revealed. The

Figure 1: The VoiPT workflow



role of the research assistant (s), to the right (Boxes, 3,4,5) are new source selection, evidence collection and coding.

A second core aspect of this methodology is a laser-like focus on causal links and mechanisms. The methodology is designed to support process tracing or causal process observation: the identification of causal mechanisms in a given case. A causal mechanism typically comprises a set of causal links that can be combined together into a single causal diagram: e.g., see figure 2 below. The clarity and rigor of process tracing would clearly be advanced not only by precision in such causal mechanism figures, and by more transparency about the evidence supporting the proposed causal links embodied in them.

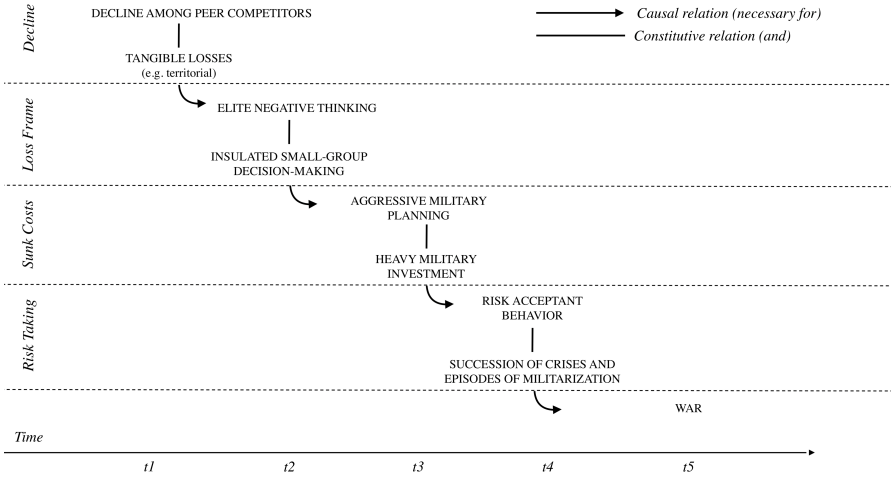
We think the veil of ignorance methodology can be applied to the use of a variety of sources that social scientists use in qualitative work. These include:

- Open-ended interviews – including elite interviews – and focus groups
- Archival sources including internal memoranda, diplomatic cables, committee reports, meeting minutes, letters, etc.
- Secondary sources, primarily academic books and articles but extending to policy analysis and journalistic accounts as well.

Most of the research conducted by the QuIP has relied on interviews with subjects of policy interventions, here we emphasize the potential for this approach to be used in studies that rely on primary and secondary sources as well. We illustrate this with reference to a recent study of the Malvinas-Falkland War based on release of new archival evidence (Schenoni et al., forthcoming) and extend it to the use of secondary sources by considering the method employed in Levitsky and Way's (2010) *Competitive authoritarianism*. We conclude this essay with an evaluation of how the veil of ignorance methodology might contribute to meeting the standards for causal process observation outlined by Bennett and Checkel (2014) and overview how it fits into the larger multi-method research enterprise.

Figure 2: Causal mechanisms in individual cases: causes of the Malvinas-Falklands war

Figure 1. Mechanism Linking Power Shifts with War



Veil of Ignorance I: selecting data sources

The veil of ignorance methodology involves coding causal claims in what we call the sources, whether primary or secondary. In the QuIP, the sources are intended beneficiaries of development interventions, who are sampled for interviews or to participate in focus groups to generate narrative data. This data is used to inductively identify recurring causal claims and stories of change, and to confront the prior theory underpinning the project intervention. Where possible, QuIP data collection entails "blindfolding" both field interviewers and interviewees from knowledge of this prior theory, in order that it does not frame and bias what they say. In particular, interviewers are not briefed about the theory, hypothesis or precise causal mechanism being tested, but are informed only about the outcomes of interest.

The QUIP experience prompted us to review how else 'blindfolding' or veils of ignorance might be used to improve the credibility of process tracing. In this paper we identify at least two other opportunities for the veiling approach. First, there is the formal process of selecting sources of evidence from a wider set of possible sources (Step 3 in Figure 1). Rigor here entails full transparency about selection criteria and procedures to avoid cherry-picking those sources most favorable to a particular theory or

causal mechanism. Second, the task of identifying causal claims embedded in selected sources (Step 5 in Figure 1) can be delegated to a research assistant without knowledge of the principal researcher's favored theories. These two opportunities are discussed in turn in this and the next section.

A central challenge in selecting the best sources is to establish their potential relevance to specified outcomes without being influenced by prior expectations about what causal claims they might advance. A core principle behind the QuIP is that the intended beneficiaries of a development intervention are themselves important informants about what has happened to them and why. The main challenge is to establish clear criteria for selecting a sample of them to be interviewed in a way that minimizes selection of those most keen to please (e.g. friends of project staff) or indeed to complain. At the very least, transparency is required about how the selection process was made, including reflection on any possible biases.

Elite interviews, as well as archival and secondary research also typically involves some form of sampling from a larger pool of potential sources, based on prior expectations about which actors are significant. In all cases, the priority is to be transparent about how the selection was made and why, a principle also embodied in guidelines for conducting systematic literature reviews and meta-analysis. For example, the Malivas-Falkland study by Schenoni et al. (2019) was prompted partly by the availability of a previously embargoed archive of interviews with military informants, providing an opportunity to revisit literature that had relied on one clearly political and partial synthesis of this material. As with the structuring of an open-ended interview, the credibility of the selection of primary and secondary sources can similarly be enhanced by establishing clear ex ante guidelines.

Thus the first veil is between the researcher and the agent who is choosing the sources to be coded. The purpose is to reduce bias in source selection. In selection of interview subjects, randomization can assist in this process. But the proposed method here goes farther: ideally the agent knows nothing about the theory, ideas, or hypotheses of the researcher. Rather, the veiled source agent is provided with guidelines about what constitutes a credible source.

Veil of Ignorance II: coding causal links

To state the obvious, the quality of the sources is very important, but this is no different than any quantitative or statistical analysis, including experiments. The second veiling procedure addresses a particular source of bias that arises in process tracing: that the researcher is the one extracting causal claims from the data. In the veil of ignorance methodology, the principal

researcher instructs an agent, who we will call the "coder" to undertake a series of steps designed to extract causal information from the sources. By shielding the coder from the favored causal theory or hunch, the researcher can be assured of a less biased array of raw data that can be used to construct or test causal process accounts. This is the veil of ignorance II.

The Veil of Ignorance II rests on structuring the relationship between the researcher and coder. Typically, research assistants are cognizant of the aims of a project. For the process described here to be neutral with respect to potential sources of bias, the coder cannot be familiar with the theory-testing objectives of the project and need not even be familiar with the empirical field in question; indeed, the method benefits from the coder operating behind a veil of ignorance that assures neutrality.

With the QuIP, the main blindfolding action takes place in data collection: field researchers ideally know nothing about the development project being evaluated. They ask respondents relatively open questions about important changes in their lives in specified outcome domains, and why they occurred. However they do so without reference to the treatment (typically a development project). It is up to the respondents to volunteer whether the project had an impact on their lives, and in an interview context that encourages them to give equal weight to other potential causal drivers.

When it comes to coding, QuIP passes the primary data onto an analyst who performs two separate coding functions: exploratory and confirmatory. The exploratory task entails purely inductive coding of causal claims (Lego blocks) embedded in the primary text (an interview transcript). To do this they need no knowledge of the project being evaluated; indeed ignorance of this enhances the credibility of the coding as a test of the project's influence. This is the coding activity which parallels the veil of ignorance II method, and can be equated with theory-building process tracing.

As part of the QuIP the coder is also unblindfolded in order to code causal claims deductively against those built into the theory of change of the development project being evaluated. This confirmatory role is similar to theory-testing process tracing. The two roles – blindfolded exploratory coding and unblindfolded confirmatory coding - can in principle be separated. Usually we envision a process in which the coder would be informed of the key outcome or outcomes (dependent variables) being investigated, and asked to report all causal statements about the factors leading to it.

Note that the instructions to the coder are designed to veil the postulated causal relationships of interest to permit a review of the full array of causal claims that may emerge from the underlying data. The second veil has the interesting corollary that ideal coders should come from somewhat distant substantive areas. Coders need to be familiar with the logic of social science, but ideally not with the specifics of the given subfield in which the process

tracing work is being done. In the case study of the Malvinas-Falklands War, for example, the research assistant would not be aware of the rival theories to explain why Argentinian government chose to take military action when it did.

Conceptualizing and coding causal claims

What are the causal claim Lego blocks that constitute potential components of a postulated causal mechanism? In this section we outline the variety of causal claims to be coded for a given event. We start with the simple X causes Y and then proceed to more complex causal claims. As necessary, we or others might add other causal relationships that are central in different substantive domains. In that sense we consider this the start but not the finish of considering the types of Lego blocks in our causal mechanism construction set.

What is it exactly, that the coder is doing behind their veil of ignorance? With QuIP studies, the relevant causal claims appear in respondents' interpretations of changes in different dimensions of their wellbeing within a specified period. They may also offer a string of claims, each cause prompted by a succession of "why" questions. In archival research, the claims in question are contemporaneous or ex-post assessments of key decision-makers or stakeholders about the causes of specific events, including their own motivation and that of other protagonists (for example, in a strategic game).

In secondary research, the coder is asked to review claims in extant sources about the causes of the outcome in question, again without bias with respect to any particular claim. An example can be given by showing how the veil-of-ignorance approach might be used not only to test propositions through the use of secondary sources but to evaluate existing tests. In their outstanding book *Competitive authoritarianism*, Levitsky and Way provide numerous case studies testing the causal mechanisms they propose. For example, in a chapter devoted to the effects of "linkage and leverage" in Europe, they offer a case study of Slovakia that runs to just over six pages and draws on over two dozen sources. The purpose is to show how linkage with Western Europe served to limit the abuses of the Meciar government (1993–1998) – a competitive authoritarian regime – and ultimately to its downfall.

The sources include books and articles from reputable field and regional journals. These sources are used to outline the fact record but also to buttress particular causal claims Levitsky and Way make with respect to the Meciar regime. But we can imagine a veiled design in which a coder was instructed to select sources on Slovakia, choosing secondary materials meeting assigned quality or credibility standards and focused broadly on

the transition from Communism in Slovakia and the Meciar regime in particular. The coder would be asked to extract the causal claims – the Lego blocks in our terminology–those sources make about the conduct of the Meciar regime and its fall. What causal arguments does a wide sampling of secondary sources actually support? Do they support the "linkage and leverage" claims made by Levitsky and Way, even if not their primary focus? Or do they support alternative interpretations? Such a process would increase confidence in Levitsky and Way's highly plausible interpretation but also identify interpretations and data that might constitute alternatives, confounds or admitted variables.

An example drawing on primary sources is the causal map of the Malvinas-Falkland War drawn by Schenoni et al. (2019), which identifies a chain of seven causes, and distinguishes between two types of links between them: causal relations (drawn as unidirectional arrows), and constitutive or definitional relations between pairs of causes (drawn as simple lines). A more complete list of causal attributions that could be coded include the following:

1. Whether the relationship is positive or negative.
2. Explicit claims that X is *not* a cause of Y.
3. Whether X is necessary or sufficient.
4. Complementary or jointly-necessary causes (interaction terms).
5. Mediator and moderator relationships (e.g. Z mediates the causal relationship between X and Y).
6. Strength of the relationship (e.g., weak, strong).
7. Certainty about the causal claim.
8. Positive versus negative feedback among component causal elements (which can also be drawn as a double arrow)

We think this is a pretty complete list, but it is easy to imagine further extensions depending on the issue in question: how narrowly defined causal processes are in time and space, and whether they refer to measurable variables, general conditions, or discrete events (as is common with most QuIP studies, which are based on asking people to identify drivers of change in specified outcome variables within a specified time-period).

It is important to realize that this approach marks a fundamental departure from traditional process tracing. Typically process tracing involves

evaluating large-scale and complex explanations; that is, indeed, its purported advantage. *The veiling methodology produces elements of a causal mechanism and not the causal mechanism itself*. That is why we call these elements Lego blocks. The principal researcher and others have the job of making sense of these elements, considering how they can be put together or aggregated, and then evaluating whether they conform with different theories and postulated causal mechanisms (Box 5 in Figure 1).

Integration: building and evaluating causal mechanisms

As we have seen, the coder provides the principal researcher with a set of causal statements related to the outcome or dependent variable of interest. These claims may converge on a single-favored explanation, but will more typically consist of an array of causal claims that ultimately have to be sorted in some way. This final process is of course the most consequential, but it is important to recognize that the interpretation of findings is a necessary stage in quantitative designs as well, even those as simple as a pure experiment in which the researcher reports a difference of means between a treated and control group. How, in the end, should we assess the coefficient in a standard regression design, for example, if it is statistically significant but not substantively so or if other factors weigh more heavily on the outcome?

At the most basic level, the coder has provided the researcher with the incidence of causal claims in the data, in the form of a set of Lego blocks. The simplest question is therefore to see whether the favored causal explanation or mechanism is supported by them. We can imagine a causal claim extraction process in which a preponderance of the underlying sources (whether respondents, decision-makers or secondary sources) tend to converge on the favored mechanism. Conversely, we can imagine a "no results" outcome in which the favored explanation does not receive support, either because there is a confounding explanation which exerts a stronger causal effect or simply because the postulated causal process essentially yields no results: a scattered pattern of causal statements that do not converge around the favored mechanism. Note that if this possibility is not allowed, then the process is from the start prone to bias. A third, possible scenario entails making a choice between rival mechanisms in which both are revealed to have some weight.

Here is a core and fundamental difference between our process tracing methodology and most others. The veiling and coding process provides the raw material for the construction of causal mechanisms and explanations as well as the evaluation of existing ones. *It does not provide a causal explanation or mechanism itself.* Thus the major work of the researcher begins with the analysis of the raw causal claim data. Much will depend on the framework

and interests of the researcher. She could be interested in an inductive explanation and mechanism that fits the data. Or she could be interested in evaluating existing or competing causal explanations of the operation of the proposed cause.

In important ways, this integration lies outside our methodology because it must be dependent on the substance in the case and the research interests involved. Nonetheless, we can think of our methodology using the common detective metaphor. It is quite safe to say that most people in the process tracing methodology literature have used the Sherlock Holmes, detective metaphor to describe process tracing. Collier's (2011) discussion of process tracing explicitly uses a Sherlock Holmes story. One can think of the Lego blocks as clues in that metaphor. The veil of ignorance I produces source material, aka clues. The detective must then integrate them into a causal story that is coherent with the clues. In the integration phase the detective might then go back to the source material to look for specific evidence missing from the raw data (clues) but which might prove critical in the complete causal mechanism. The advantage to this process is that it is transparent about which causal clues originate from the researcher and which form the basic causal claim dataset.

How does the veil of ignorance methodology fare against the Bennett and Checkel checklist?

We use Bennett and Checkel's list (2014, 21) of desirable features for any process tracing methodology as a framework for discussion and evaluation of the veil of ignorance methodology. We propose that the veil of ignorance methodology deals quite well with many of the items on this list (see also Bath Social and Development Research, n.d. table 3.)

1. Cast the net widely for alternative explanations.

The core principle for the source agent is to locate sources with some level of a priori credibility of their causal accounts. Since the agent does not know the theory in question the net is cast widely in terms of a variety of sources. This can be handled in part through randomization with respect to open-ended interview subjects, but requires more thought in selection of primary and secondary sources. The method encourages source selection that avoids ideological and political as well as disciplinary bias.

2. Be equally tough on the alternative explanations.

Because the causal claim coder does not know the alternative explanations there is no way for her to be tough or easy on any of them.

3. Consider the potential biases of evidentiary sources.

Given that the source agent does not know the theory under investigation it is hard for her to have any significant bias. The purpose of the veiling is to

choose a wide-ranging list of credible sources so as to minimize and reduce bias. The methodology does not consider biases in the sources themselves, but this is at least partly obviated by the choosing of multiple and diverse sources.

4. Take into account whether the case is most or least likely for alternative explanations.

The veils of ignorance prevent the coder from knowing anything about the potential explanations under consideration. The role of the researcher during the integration phase is then to assess which possible explanation is most consistent with the Lego block evidence supplied by the causal claim data.

5. Make a justifiable decision on when to start.

A core question for any causal process observation is when in time one should start the analysis. While it obviously will depend on the specific case being explained, the causal claims themselves can suggest a beginning point. One would probably not want to begin at a point before or after many causal claims in the data set.

6. Be relentless in gathering diverse and relevant evidence, but make a justifiable decision on when to stop.

The veil of ignorance approach clearly incentivizes such a process.

7. Combine process tracing with case comparisons when useful for the research goal and feasible.

The veil of ignorance causal mechanism methodology is about within-case causal inference, but there is no reason why this method could not be extended to those favoring small-N qualitative comparative analysis.

8. Be open to inductive insights.

Obviously the causal claims themselves constitute precisely inductive insights. They may be features of the causal mechanism that were not obvious to the researcher beforehand. As a result, the sources can be systematically mined for insights because they do not depend on the pre-existing positions of the researcher.

9. Use deduction to ask "if my explanation is true, what will be the specific process leading to the outcome?"

Core to the Bayesian approach is the prior belief in the hypothesis under consideration vis-à-vis its alternatives. Absolutely central to the veiling procedure is that the collection and initial compilation of evidence is not subject to priors at all. In Bayesian terms this becomes a uniform prior. One does not explicitly consider alternative explanations and mechanisms until the basic raw causal claim data are delivered to the researcher. At this point of course the various alternatives are considered in the integration phase to produce a conclusion.

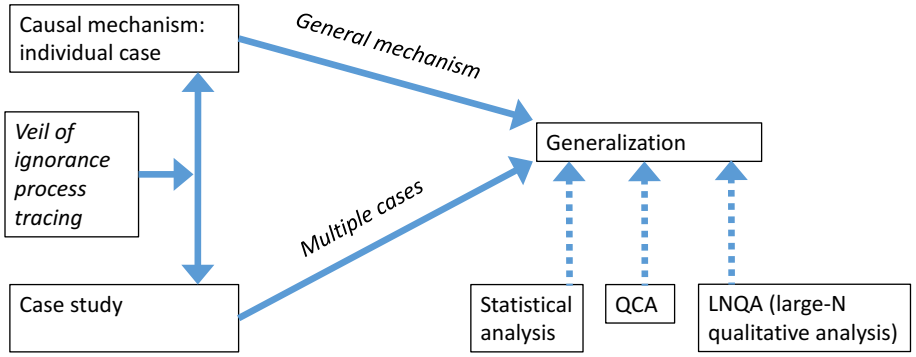
10. Remember that conclusive process tracing is good, but not all good process tracing is conclusive.

As with all data, there is no guarantee that the results will be conclusive. It might be that the causal claims fit naturally into one coherent causal mechanism. But it is also quite possible that there are multiple mechanisms that are consistent with the basic causal claim data.

11. Process tracing should be transparent.

This last item is our addition to the Bennett and Checkel list, which we consider both as important and noncontroversial. Generating a specific and comprehensive list of sources, the explicit coding of causal claims, and the generation of causal mechanisms figures makes the methodology very transparent.

Figure 3: VoiPT in the research triad: generalization issues



Conclusion

This paper has introduced and proposed a methodology for within-case causal inference: the veil of ignorance process tracing methodology.

The Veils of Ignorance provide some practical steps for making process tracing more rigorous and transparent. A core idea is to use a veil of ignorance to address potential bias in selection and coding of data for building and testing causal theories. We have explained how this entails introducing a more explicit division of roles within the research process between a lead researcher and research assistants delegated blindfolded responsibility for aspects of data selection and coding. We have also suggested that there is scope for applying a clearer and stronger set of rules and principles for recording the strength and direction of empirically derived causal claims as an intermediate step towards constructing causal mechanism figures.

These proposals draw inspiration and strength from recent experience using the QuIP to evaluate the impact of over forty development projects. In addition we believe that the QuIP software provides a useful start for visualizing and integrating causal claims.

Looking at the eleven criteria for good process tracing discussed above we think that the veil of ignorance approach has significant promise. It deals quite effectively with a majority of the criteria in that list. About one-third deal with features that lie outside the veil of ignorance methodology and in what we call the integration phase. The whole point of the veil of ignorance methodology is that the researcher does not know the alternative explanations under examination.

The methodology generates a list of causal claims that then must be integrated by the researcher. This constitutes quite a different approach to process tracing than those where the researcher is not only choosing the sources, but the causal claims in the sources, and then putting them together in a causal explanation. The veil of ignorance methodology radically separates these two parts of process tracing, the causal claims raw data from the integration into mechanisms. We believe that this constitutes a better basis for evaluating alternative explanations than current methodologies in the process tracing literature.

One might object that this methodology involves a tremendous amount of effort in order to do a causal analysis of an individual case and it would not be practical in for books such as *Competitive authoritarianism*. This raises the question of how an individual-case causal mechanism analysis fits into some larger research project. Figure 3 illustrates how we see this methodology as being connected with some larger research enterprise. We see multimethod research as involving three core components that are part of what might be called the research triad. Most social scientists are not interested in the explanation of individual cases as much as generalizable theories which apply to many cases.

The first generalization issue arises in asking how generalizable the case to other cases within the scope or population (the lower arrow in figure 3). Qualitative analysis can contribute to this goal through QCA or other cross-case qualitative methods. Generalizability can also be achieved by multiplying the number of case studies. Goertz and Haggard (2019) call this large-N qualitative analysis (LNQA) which involves a separate methodology, but one which links out naturally with the veil of ignorance outlined here. For example, one might do a couple of Veil of Ignorance analyses combined with much more superficial case studies (e.g., Ziblatt 2017 uses this kind of case selection strategy).

The goal of the veil of ignorance methodology is causal mechanism analysis in individual cases. The top arrow leads from the from the specific causal mechanism in the case to a general causal mechanism. We consider this relatively unexplored terrain. One could imagine that the causal mechanism figures for several cases might involve specific features of those cases. The general causal mechanism might require turning those specific features into more general factors that apply in multiple settings. Often theory testing moves in the other direction from some general mechanism to the individual case. These reflect the inductive versus testing mode of using the Veil of Ignorance methodology. We suspect that in practice there will be a dialogue between the two, the specific and the general.

It goes without saying that the ability to generalize from cases both theoretically and empirically will depend on getting those cases right, which the veil of ignorance approach is designed to achieve.

References

Bath Social and Development Research, n.d. The Qualitative Impact Assessment Protocol. BSDR Briefing paper. www.bathsdr.org.

Bennett, A., and Checkel, J. (eds.). 2014. *Process tracing in the social sciences: from metaphor to analytic tool.* Cambridge: Cambridge University Press.

Collier, D. 2011. Understanding process tracing. *PS: Political Science & Politics* 44:823–30.

Copestake, J., Morsink, M., and Remnant, F. 2019. *Attributing development impact: the qualitative impact protocol case book*. Rugby: Practical Action Publishing.

Fairfield, T., and Charman, A. 2017. Explicit Bayesian analysis for process tracing: guidelines, opportunities, and caveats. *Political Analysis* 25:363–80.

Goertz, G. and Haggard, S. 2019. Generalization, case studies, and within-case causal inference: Large-N Qualitative Analysis (LNQA). Manuscript.

Levitsky, S., and Way, L. 2010. *Competitive authoritarianism: hybrid regimes after the Cold War.* Cambridge: Cambridge University Press.

Schenoni, L., Braniff, S., and Battaglino, J. forthcoming. Was the Malvinas/Falklands a diversionary war? A prospect-theory reinterpretation of Argentina's decline. *Security Studies*.

Waldner, D. 2015. Process tracing and qualitative causal inference. *Security Studies* 24:239–50.

Ziblatt, D. 2017. *Conservative parties and the birth of democracy.* Cambridge: Cambridge University Press.